Comparative Modelling of Interregional Transport Flows Applications to Multimodal European Freight Transport

Nijkamp, P.; Reggiani, A.; Tsang, W.F.

1999

COMPARATIVE MODELLING OF INTERREGIONAL TRANSPORT FLOWS

Applications to Multimodal European Freight Transport

Peter Nijkamp
Aura Reggiani
Wai Fai Tsang

Research Memorandum 1999 – 2

vrije Universiteit amsterdam

COMPARATIVE MODELLING OF INTERREGIONAL TRANSPORT FLOWS
Applications to Multimodal European Freight Transport

Peter Nijkamp[a)], Aura Reggiani[b)] and Wai Fai Tsang[a)]

a) Department of Spatial Economics, Free University, Amsterdam

b) Department of Economics, Faculty of Statistics, University of Bologna, Bologna

Abstract

This paper aims to compare the descriptive and predictive power of two classes of statistical estimation models for multimodal network flows, viz. the logit model and the neural network model. The application concerns a large data set on inter-regional European freight flows for two commodity categories (food and chemicals). After an exposition of policy issues, methodological and modelling questions and the database, a variety of experiments is carried out. The results show that in general the predictive potential of neural network models is higher than that of logit analysis. The statistical results are also used to investigate the implications of various road tax systems (e.g., ecotaxes) on various segments of the European road network

1. Changes in the European Freight Transport Scene

1.1 Introduction

After the completion of the European market and with the widening of Europe towards easterly direction, mobility in general has shown a steady increase in Europe. In particular, cross-border transport has been at a rising edge with annual growth rates exceeding sometimes 10 percent, a process reinforced by the current globalisation trends. The integration of former segmented markets - and the related liberalisation in the European space - has led to drastic changes in goods and passenger transport. It is expected that the demand for all forms of transport in the EU will continue to rise up to the year 2010, so that a further increase in goods transport of some 70 percent seems to be likely. This trend is explained by a number of factors (see ECMT, 1995 and Banister, *et al.*, 1993):

- an upturn in economic and industrial activity;
- enlargement of the EU and co-operation with the European Free Trade Association (EFTA); more transit flows from the South of the EU and the developments in Eastern Europe will lead to more trade, both intra-European and international;
- increased globalisation and intemationalisation of economic activity.

Europe will hence face a series of transportation problems, which may hamper its competitive position. This calls for a Europe-wide policy. Co-ordination at the European level regarding the transport sector is necessary in order to cope with this growth, viz. a common transport policy (CTP). One of the elements of the CTP is the development of Trans-European Networks (TENs), which will contribute to a more efficiently running transport system (e.g., removing bottlenecks) and will induce more cohesion in the EU; goods, people and information will then travel more freely.

As a result, there is an increasing interest in the issue of intermodal competition and complementarity. For surface transport in Europe, especially the competitive position of rail vis-a-vis road is at stake. This holds increasingly also for commodity transport, It needs to be added however, that the analysis of freight transport in Europe is fraught with many difficulties, as freight is not a homogeneous commodity, but is composed of an extremely diversified set of goods with specific haulage requirements and logistic needs. This means that a commodity-specific approach is necessary to analyse in depth the implications of changes in network configurations. To offer a background scene, we will first concisely describe the rail and road network in Europe.

1.2 Rail Network

Initially, European rail policy has emphasised the need for an efficient management of railway undertakings based on normal business principles (see Kiriazidis, 1994). But in 1991, the EU recognised the critical role of rail transport in satisfying the EU's transport needs. The following objectives were stated:

- introduce commercial principles in the railway sector;
- allow free access to national railway networks;
- eliminate the large capital debts of railways undertakings;
- enable competition in transport services across national borders.

To achieve these objectives, the EU implemented a plan to separate the rail management from the provision of services. Although free access and competition in the railway sector can generate considerable efficiency gains, a disadvantage may be that some less profitable services may be discontinued.

In the area of passenger transport, a high-speed European rail network is considered as a proper infrastructure provision that meets rising transportation demand and environmental sustainability conditions. The order of magnitude of distances and population distribution in the European area is believed to offer an ideal condition for the development of this high-speed rail network. European railway policy is largely based on upgrading the existing rail network, where missing links between the national rail networks are connected and where the existing rail is upgraded to the conditions for high-speed rail (for example, the Channel Tunnel rail link connects the railways of Great Britain and the rest of Europe). A major difficulty in the development of the high-speed rail network is the interoperability, in particular the technical harmonisation. There have been national high-speed rail projects developed with different engineering standards; for example, the high-speed rail system of Germany (ICE) is also suitable for heavy goods transport, while the French high-speed rail (TGV) is developed for 'light' passenger transport. But also in cases where dedicated high-speed lines are developed, there is a gain for the freight sector, as the existing lines offer then more free capacity for goods transported by rail.

1.3 Road Network

Until 1983, the EU members protected their national transport sector and - as a result - the progress towards a common transport policy was slow. But slowly, several steps towards liberalisation and deregulation in the transport sector have been taken. Before 1993, intra-EU transportation was controlled by bilateral quotas and cabotage was only scarcely permitted. In 1993 all quotas were abolished, but cabotage was still limited. These limitations according to plan will be removed in 1998. As mentioned before, the demand for transport services has increased sharply and a major part of this growth may be found in road transport. In order to meet this increasing demand, a plan for a Trans-European road network has been developed. The plan for the Trans-European road network incorporates existing national networks and provides for the development of new networks where their absence causes isolation or prevents the development of part of the EU territory. The following actions have been recognised by the EU Commission:

- the construction of missing stretches of roads and the improvement of the existing ones so that they are fully accessible and coherent across the EU;
- the improvement of the interoperability of the network (harmonisation of technical aspects like road signs and signals) in order to ensure its total efficiency at the EU level.

One of the objectives of this TEN is to offer border / peripheral regions (and countries) the necessary infrastructure conditions to grow due to a better connection with the rest of Europe. This leads to greater social cohesion, which will contribute to an efficient and competitive economic area. But the bulk of transport flows goes through the main / central regions and if insufficient investment is made in the core regions, these areas will become bottlenecks (e.g., congestion and environmental pollution). The EU is faced with the problem to find the right balance between these two strategies.

A number of countries (i.e., Switzerland, Austria, etc) provide the main transport corridors for the EU. They are facing relatively high transport costs, maintenance costs and external cost such as air pollution and therefore they are in the mean time discouraging road transport and promoting rail transport.

1.4 Concluding Remarks

The EU acknowledges the need for a TEN and is planning to construct this by connecting the existing national transport networks. This TEN should improve the accessibility of European regions, while paying attention to environmental restrictions. The issue of central and

peripheral areas is also important: investments are mainly undertaken in the central areas, because they contribute to the economic growth more than investments made in peripheral areas. On the other hand, social cohesion is necessary for economic growth and investment is needed to connect the peripheral areas. Clearly, the TENs face interoperability problems: technical, social and fiscal harmonisation of the differences between EU member states.
A possible way of monitoring the emerging EU flow patterns is the use of forecast / sensitivity scenarios based on specific transport models. The paper explores this research direction by offering a comparative empirical study of the performance of two classes of models (viz. logit models and neural neural network models) in the light of their applicability in the European freight transport sector.
The paper is then organised as follows: Section 2 illustrates the analytical approaches adopted for the empirical analysis, while Section 3 describes the European database on freight flows. Section 4 and 5 describe the results emerging from the calibration / training process for the logit and neural network model, respectively. Section 6 offers a comparison of these results, by implementing also a sensitivity analysis based on different tax policy scenarios. Finally, Section 7 will conclude the paper with some methodological reflections.

2. Analytical Approaches to Transport Networks

In this section we will briefly describe two major promising analytical approaches to transport networks, viz. logit analysis and neural networks analysis. They will be applied to our specific case study of the European freight transport sector.

2.1 Logit Models

The early transportation applications of discrete choice models were made for the binary choice of travel mode (where the options are restricted to two choices) and were mainly focused on the estimation of a value for travel time, which was then used in order to calculate the monetary value of travel time savings. In the 1970s research focused on the mode choice with multiple options and other travel related choices such as trip destination. At present, the logit model has become a widely adopted approach for modal split analysis of multiple choices. Recent experiments using logit models and related spatial interaction models in order to map out the freight transport in Europe have been carried out by Tavasszy (1996), who showed the suitability of logit models also for the goods transport sector (where data are often more 'fuzzy' and incomplete compared to the passenger sector).
Logit models are discrete choice models, which are used for modelling a choice from a set of mutually exclusive and exhaustive alternatives. It is assumed that the decision-maker chooses the alternative with the highest utility among the set of alternatives. The utility of an alternative is determined by a utility function, which consists of independent attributes of the alternative concerned and the relevant parameters. In a logit approach the concept of random utility is adopted, which means that the true utilities of the alternatives are considered to be random variables, i.e.,

$$U_{in} = f(X_{i,s}) + \varepsilon_{in} \tag{1}$$

where:

U_{in} = the utility of alternative i for individual n;
$f(X_{i,s})$ = a function of attributes s related to alternative i;
ε_{in} = a random disturbance term.

By maximising then the stochastic utility (1), the probability that an alternative is chosen is defined as the probability that it has the highest utility among all relevant alternatives (see e.g. Ben-Akiva and Lerman, 1985, Cramer, 1991 and McFadden, 1977). Then the following assumption is made concerning the random term:

$$F(\varepsilon_n) = \frac{1}{1+e^{-\mu\varepsilon_n}} \qquad \mu > 0, \quad -\infty < \varepsilon_n < \infty, \tag{2}$$

$$f(\varepsilon_n) = \frac{\mu e^{-\mu\varepsilon_n}}{(1+e^{-\mu\varepsilon_n})^2} \tag{3}$$

For the sake of convenience, usually the assumption is made that $\mu = 1$. The logit model has become in the mean time a standard analytical tool in discrete choice modelling. The logit model adopted for our empirical analysis has the following form:

$$P_{ij}^m = \frac{\exp(U_{ij}^m)}{\sum_m \exp(U_{ij}^m)} \tag{4}$$

where:

$$U_{ij}^m = \sum_z \beta_z X_{z,ij}^m \qquad z = 1,...n \tag{5}$$

m = the mode of transport (m = rail or truck);

P_{ij}^m = the probability of choosing the mode *m* from region i to region j ($i \neq j$);

U_{ij}^m = the utility connected with the mode *m* on the link (ij);

$X_{z,ij}^m$ = the vector of attributes z for mode *m* in the utility function for the link (ij) (in our case the attributes are 'cost' and 'time' / 'distance');

β_z = the vector of parameters related to the vector of attributes time and cost.

The logit model can at present easily be estimated by means of standard statistical software.

2.2 Neural Networks

2.2.1 A brief historical introduction

The functioning of the human brain and nervous system, which is capable of performing complex tasks (recognise a face, for instance), has inspired scientists in developing a model of computation known as parallel distributed processing, or artificial neural networks (ANN[1]). In recent years NNs have become a popular analysis tool and have been widely applied to the area of transport engineering, particularly in relation to traffic control problems and accidents (see Himanen et *al.*, 1998). However, only a few experiments exist in the field of transport economics (see Nijkamp *et al.*, 1996 and Schintler and Olurotimi, 1998).

In 1943, McCulloch and Pitts proposed the first mathematical model of a neural network[2] and proved that, theoretically, any logical function could be represented with this connectionist

[1] ANN will be further referred to as NN.

[2] This neural network model consisted of neurons that can only have two values (i.e. binary) and did not have the ability to learn

approach. They also introduced the concepts of threshold functions and weighted sums, which are commonly adopted in NNs. About six years later, Hebb (1949) presented a mathematical procedure for machine learning, the Hebbian learning; neural pathways are strengthened each time they are used. In 1962, Rosenblatt successfully developed a perceptron network model; it computes a weighted sum of the inputs, then subtracts a threshold value from that and provides an output value. This mechanical model is capable of recognising the letters of the English alphabet. Since the perceptron models have a rather simple structure, the learning procedure used to train these models is simplified. Following this, much research on perceptron models has been done. Different types of NN were also studied, for example the multi-layer machine MADALINE, which eliminates the echoes on phone lines. In 1969, Minsky and Papert marked a turning point in the development and the study of NNs, when they showed in their book that the perceptron network could not solve problems that were non-linear separable. Several researchers became disappointed and most of them left the field. However, research on the multi-layer perceptron and error back-propagation algorithm in the 1980's continued, which let to a renewed interest in NN. Cybenko (1988) showed that any continuous function could be represented by a multi-layer NN with one hidden layer and even any function with just two hidden layers. A further extension was the principle of competitive learning (see Kohonen, 1989), which is adopted in self-organisation and associative memory models. These models are able to learn by itself without the need of corrections of an external teacher. The next subsection will describe such NN approaches in more detail.

2.2.2 Characteristics of a neural network

The knowledge and insights in the working of the human nervous system and the human brain have inspired theories of neural network modelling. An NN is a network of neuron cells that are connected with each other with axons and dendrites. The neuron cells send electrical signals through these connections. Analogously, in ,a NN structure artificial ***neurons*** (computational elements) are connected with each other through a pre-determined pattern of connections. Instead of electrical signals a value ***(activation value)*** is sent through these connections. Each connection has a numeric ***weight*** associated with it. Weights are the primary means of long term storage in NNs and learning usually takes place by updating the weights. Some of the units are connected to the external environment, and can be designated as input or output units. The weights are modified so as to bring the network's input / output behaviour more into line with that of the environment providing the inputs. The ***structure*** of a generic NN can be divided in three levels (see e.g. Reggiani *et al.*, 1997):

- micro structure: the activation / behaviour of a single neuron;
- meso structure: the physical organisation of the neurons;
- macro structure: the union of different meso structures to solve complicated problems.

The way the neurons are connected mainly determines the way it will behave and how it needs to be trained. A widely used type of NN is the feed-forward NN. In a feed-forward NN each neuron is only connected to neurons in the next layer and there are no connections between neurons from the same layer. If each neuron is connected with every neuron from the next layer, it is called fully connected. These networks are relatively well understood and easy to train, since all computations are in one direction; from the input to the output layer and there are no back-cycles or time lags. They will also be used in our experiments illustrated in Sections 5 and 6.

2.2.3 Training a neural network

During the learning process of the NN model, the network will adjust its weights every time it receives an input in order to learn and produce the right output. The weights contain the ‘knowledge’, but they are not as easily understood as in the case of normal (linear) regression models. There are two learning methodologies: if the NN is presented both the input and the desired output during its training process, it is called supervised learning[3]. In the case of unsupervised learning, the NN has to decide on its own what the desired output should be and when to stop the training procedure, since only inputs are provided. Related to this learning rule, is the overfitting problem, which will be discussed later on (see e.g. Fischer, 1998).

The majority of the NN models applied in empirical studies uses the supervised learning, where the actual output of the NN is compared to the desired output. At the beginning of the learning process, the weights are set randomly. The objective is to minimise the error of all processing elements by adjusting the weights. At each iteration, the model adjusts its weights in order to have the actual output closer to the desired output. When an acceptable network accuracy is reached, the model will stop the learning process.

With supervised learning - like in our study - , the NN is presented with input data and the corresponding output data during the training process. This data set is often called the training set. This training process can take much time depending on the processing power, the amount of data and the predefmed performance level, at which the training process will stop. When no further learning is required, the weights are fixed for testing and the trained NN model can be applied to new data. Some NNs are allowed to adjust its weights when it is operating, so that it will adapt to changing conditions.

The NN needs to be tested after training to see how well it can handle data, which it has not yet seen. A test set is used for this purpose. If its performance is not reasonable, then it has not been trained well. But it is also possible that it has learned to map the training set exactly, including incorrect information /noise, instead of the general pattern. Then the NN model has to be trained all over again.

This learning methodology is limited to self-organising networks (recurrent NNs). These NNs use no external influences to adjust their weights. Instead they internally monitor their performance. These networks look for regularities in the input signals and make adjustments to its activation pattern. Depending on the structure of the NN and on the learning rules, it knows how and when to adjust. An unsupervised learning algorithm might be that, when a neuron is activated by an external input, the whole cluster of neurons to which it belongs would have an increased activity level. Also competition between processing elements could form a basis for learning. When competition for learning is in effect, only the weights belonging to the winning processing elements will be updated. At present unsupervised learning is not yet well understood and still the subject of research.

Many learning laws are commonly used in NN models and most of them are some sort of variation of the Hebb’s Rule. The first and undoubtedly best known learning rule was introduced by Hebb. His basic rule is that if a neuron receives input from another neuron and if both have the same sign, the weight of this connection should be increased. There is still a lot of research going on in learning laws and regularly new ideas show up, as our understanding of neural processing grows.

In particular with the back-propagation learning, it is possible that the NN is learning ‘too much’. In this case the NN stores the exact pattern between the inputs and the outputs it receives during the training phase and will perfectly reproduce the desired output, given the known input. But it will perform badly, when it receives new, unknown inputs, because it is not able to generalise from its ‘knowledge’. This is called the over-fitting problem and one method in order to avoid this problem is the cross-validation technique. During the training of the NN, a different data set, the cross-validation set, is used to monitor its performance with

[3] There is also a third type of learning methodologies, viz. reinforced learning, where reinforcement is provided instead of the desired output. This can also be seen as supervised learning with less informative feedback.

unknown inputs/outputs. When the average square error of the NN related to the cross-validation set becomes worse, the training should be stopped at this point.
The application of an NN model may be considered as a process consisting of nine steps (Turban, 1995). These steps are concisely presented in Table 1.

Step	
1	Collect data
2	Separate data in a training and test-set
3	Define the structure of the NN
4	Select a learning algorithm
5	Determine the parameters and provide a start value to the weights
6	Transform data into fitting input
7	Start learning (changing the values of the weights)
8	Stop learning and test
9	Implementation (application to new data)

Table 1. The neural network modelling process

2.3 Concluding Remarks

Although the NN approach has been mainly applied in operational systems for pattern recognition, i.e. optical character recognition, speech recognition, etc., it is becoming an interesting modelling approach to other fields of research, for instance, in economics. The availability of powerful processing systems and easy-to-use software make it widely applicable. The advantage of NN over traditional modelling approaches is that it is not limited by methodological restrictions, e.g. the Independence of Irrelevant Alternatives (IIA) property. This means that an NN model can handle better complex problems than the traditional models. Data, especially transportation data, often contain noise / incorrect information, which can confuse the traditional modelling approaches and prevent them from correct calibration. However, an NN can easily deal with this kind of data 'corruption', since it can recognise the whole patterns from just a part. During learning, an NN is capable of correcting the noise by adjusting the weights, so that the total error term is minimised.
A major disadvantage of the NN models is that they are generally a 'black box'. When an NN is trained and performs reasonably, it is not clear if or how a certain variable is correlated with the output variable. Knowledge that an NN has learned during the training process is not stored in some specific region of the system, where it may be retrieved. Instead, this knowledge is somehow represented in the weights of the connections. Because an NN is a parallel distributed processing system, the value of the weights is not an indicator for a possible correlation. Schintler and Olurotimi (1998) showed that there may be some connection between feedforward, backpropagation NNs and logit models. In their work, they demonstrated that a multi-layered feedforward NN can be considered as a binary logit model with non-linearity in the parameters of the utility function. These parameters can be adapted to the data, resulting in an 'adaptive' logit model. By implementing a conceptual layer, where inputs are presented to the NN as weights, adaptive elasticities of demand can be calculated from the trained NN. This research indicates that NNs are perhaps not complete 'black boxes'. Clearly, further research in this direction is needed to make the application of NNs in social sciences more fruitful.

3. European Freight Flow Data

In Section 4 and 5, two alternative modelling approaches will be employed in order to analyse the freight flow patterns between 108 regions in Europe. Two modes of transport, i.e. road and rail mode, are considered to perform a modal split analysis. Later in Section 6, a sensitivity analysis based on policy scenarios will be presented.
In order to carry out the mentioned modal split analysis on a European level, freight flow data on a European level are needed for, which are mostly not available or not suitable. Most of the times, national sources are incompatible in structure, content and period concerned, and the information is seldom up-to-date (COST 328, 1998). The data set used for the experiments has been drawn from existing data on the national level and some limited European data using a gravity model (NEA, 1994).
The data set[4] contains the freight flows and the attributes related to each link between 108 European regions. Furthermore, the flow distribution in the matrices concerned refers to two product groups, i.e. food referred to as data set A (for the year 1986) and chemical products referred to as data set B (for the year 1990). The attributes considered ***are 'time'*** and ***'cost'*** (for data set A) and ***'cost'*** and ***'distance'*** (for data set B) between each link (ij) with reference to the transport mode, viz. the road and rail mode. In particular, each observation of the data set pertains to variables related to each link (ij). Since 108 areas have been considered, each of the two data sets should ideally contain 11664 observations. However, data set A contains finally 4409 observations and data set B 2500 observations, because of the following considerations:

- the intra-area freight flows are zero;
- for each link, only the transport movements towards one direction $i \rightarrow j$ have been considered;
- only the links where the flows and the attributes (of both road and rail) are different from zero have been considered (i.e., empty cells are excluded).

In order to test the models, each data set has been divided into two sub-sets. The first sub-set, the calibration set, has been used to calibrate the logit models and to train the NN models. The second sub-set, the test set, has been kept apart for the purpose of testing the models. The training of the NN model required a further separation of the calibration set into a training set and a cross-validation set. This cross-validation set has been used during the learning phase of the adopted NN model in order to overcome the over-learning. More precisely, the data sets have been randomly subdivided into the three sub-sets indicated in Table 2.

	Data set A	**Data set B**
Calibration set	3439	1731
Training set	2992	1481
Cross-validation set	447	250
Test set	970	769
Total	4409	2500

Table 2. The numbers of observations in each sub-set

It is evident, that reliable observation of all data is fraught with many problems, owing to un-reliable transport flow estimations, due to different and deficient national data collection

[4] The data set has been kindly provided by NEA Transport Research and Training, Rijswijk.

techniques, ambiguous regional definitions etc. By no means the data used in the experiments may claim perfect reliability.

4. The Logit Model Experiments

As mentioned before, first the binary **logit** model has been adopted to analyse the modal split problem between road and rail in relation to the interregional freight flows of food and chemical products between 108 regions in Europe.

4.1 Calibrating the Binary Logit Model

The binary **logit** model used for the experiments has the following formulation:

$$P_{ij}^{c} = \frac{\exp^{(U_{ij}^{t})}}{\exp^{(U_{ij}^{t})} + \exp^{(U_{ij}^{c})}} \tag{8}$$

where:

$$U_{ij}^{c} = \beta_1 \cdot X_{1,ij}^{c} + \beta_2 \cdot X_{2,ij}^{c} \tag{9}$$

$$U_{ij}^{t} = \beta_3 \cdot X_{1,ij}^{t} + \beta_4 \cdot X_{2,ij}^{t} \tag{10}$$

P_{ij}^{c} = the probability of using the road mode from region i to region j (i $\neq$ j),

U_{ij}^{c} = the utility connected with the road mode (c),

U_{ij}^{t} = the utility related to the rail mode (t),

$X_{1,ij}^{m}$ = the attribute 'cost' for mode m in the utility function for the link (ij),

$X_{2,ij}^{m}$ = the attribute 'time' (data set A) / 'distance' (data set B) for mode m in the utility function for the link (ij),

β_1, β_2 = the parameters related to the attributes 'cost' and 'time' / 'distance', respectively, for the road mode,

β_3, β_4 = the parameters related to the attributes 'cost' and 'time' / 'distance', respectively, for the rail mode,

The **logit** models have been utilised in order to estimate the unknown parameters in the utility function[5] using the calibration set only. The estimated parameters resulting from the calibration stage are presented in Table 3.
The goodness-of-fit of the model has been evaluated using the t-test and the R^2 indicator (see Table 3). The t-test values indicate that the parameters β_1, β_2 and β_3 (for the food freight flows) and β_3 (for the chemical freight flows) are significantly different from zero. Clearly, rail time (for the food sector) does not offer a significant explanation. In our approach, the R^2 test statistic is calculated using the calibration set and presented in Table 3 in order to evaluate the calibration. According to the R^2 indicator, both **logit** models appear to be calibrated rather well, although the results of the **logit** model for case B are less accurate.

---

[5] The statistical software, LIMDEP, has been used to estimate the binary **logit** model.

	Variables		Coefficient	std error	t-ratio
Logit model A	**Road cost**	(β_1)	-0.02424	0.4481E-02	-5.410
	Road time	(β_2)	-0.00126	0.4539E-03	-2.769
	Rail cost	(β_3)	0.05781	0.3069E-02	18.836
	Rail time	(β_4)	0.00046	0.4395E-03	1.0451
	Log likelihood value		-1148.9		
	R^2		**0.745**		
Logit model B	cost	(β_1)	0.3074E-02	3,763E-05	-0.214
	Rail **cost**	(β_3)	0.2795E-02	1,759E-05	**6.042**
	Log likelihood value		**-833.7**		
	R^2		**0.679**		

able 3. Calibration results of the logit models for data set A and B

Some further remarks are in order here. The overall statistical results of the logit model are not extremely impresive. It should also be noted that in our experiments logit model B has been calibrated only with the 'cost' attribute, because the attributes 'cost' and 'distance' appear to be highly correlated in this case. Next, inspection of the log likelihood-test indicates that when the 'distance' attribute is added to the logit model, it will not improve the logit model significantly. Apparently, this distance variable plays only a feeble explanatory role.
The results of the binary logit model can now be used to make spatial forecasts on the basis of various transport economic scenarios. For this predictive purpose, the test set, which is not used in the calibration stage, is employed. In order to analyse the spatial forecasting performance of the binary logit model, the statistical indicators R^2 and Average Relative Variance (ARV)[6] will be used. The coefficient of determination R^2 is usually adopted in the calibration procedure for logit models, while the ARV is more commonly used for neural network models (see e.g. Fischer and Gopal, 1994). However, the indicator ARV will here also be considered for the logit model in order to carry out a proper comparison with the NN approach. Both the R^2 and the ARV indicators have been calculated and are presented in Table 4. The probabilities of rail and road are used in calculating the statistical indicators.

	Logit	
	Food	**Chemicals**
ARV	0.183	0.311
R2	0.781	0.679

Table 4. Statistical indicators for both commodity groups using the test set

It should be noted that the ARV measure should ideally approach zero, while the R^2 measure should approach one, if the estimates tend to be accurate. Concerning the results presented in

[6] See Annex for the formulations of the statistical indicators.

Table 3 and 4, the logit model applied to the food sector appears to have an excellent predictive ability, while the logit model for the chemicals performs moderately[7].

5. The Neural Network Model Experiments

5.1 Introduction

In this section we will present the results of our NN approach. Reggiani and Tritapepe (1997) describe a methodological structure for the main NN modelling steps consisting of three stages:

- definition of network architecture;
- learning phase;
- forecasting phase.

As previously mentioned, in parallel with the logit approach the NN modelling approach has also been used to analyse the same modal split problem with the same data set. Particularly, two NN models have been adopted, viz. model (NN (A)) for the food sector and model (NN (B)) for the chemical products. The design of the network architecture will be given in Section 5.2. In Subsection 5.3 the NN models will be trained and evaluated. Then the spatial forecasting analysis of the two NN models will be performed and evaluated in Subsection 5.4.

5.2 Definition of Network Architecture

A feedforward NN with at least one hidden layer is able to analyse most linear and non-linear problems. Other NNs, for instance recurrent NNs, are too complex and probably less efficient for the modal split problem (i.e., a comprehensive learning procedure). Following the majority of application of NNs, a feedforward NN has been implemented in our experiment. The structure has been determined by taking into account the number of observations and by carrying out a large number of experiments. The values of the parameters have been determined by carrying out several experiments as well.
After several experiments, our two NN models have been calibrated with the following structure and parameter values (Table 5):

	Neural Network Model A	**Neural Network Model B**
Number of hidden layers	1	1
Number of hidden units	8	8
Learning rate	0.9	1
Momentum factor	0.05	0.9
Epoch size	1	1
Initial weight values	randomly between [-0.1;0.1]	randomly between [-0.1;0.1]

Table 5. Neural network parameters

These NN models will be calibrated using the training set in the next subsection.

[7] **An explanation may be that the chemical data were transformed from a different geographical scale to make them compatible with the food data.**

5.3 Training the Neural Network

In order to ease the training of the NN, the attributes time and cost, denoted by V_j, have been transformed (in a value range between [0,1]) by means of the following functions:

$$V_j^f = \exp^{(-0.002 \cdot V_j)} \tag{6.1}$$

The variables are defined as follows:

TC_{ij}^f : transformed rail cost for link (ij);
TT_{ij}^f : transformed rail time / distance for link (ij);
RC_{ij}^f : transformed road cost for link (ij);
RT_{ij}^f : transformed road time /distance for link (ij);
T_{ij} : total freight flow related to link (ij);
T_{ij}^{road} : total road flow related to link (ij);
p_{ij}^{road} : road mode probability for link (ij), in relation to the following relationship:

$$T_{ij}^{road} = p_{ij}^{road} \cdot T_{ij} \tag{6.2}$$

Since NNs are able to learn reasonably even when incomplete and noisy data are provided (in particular the chemical data), the NN model for the chemical commodity group has been trained using the 'cost' and 'distance' attributes.
In order to cope with the overfitting problem the cross-validating technique has been used. After the training of the NN models has been completed, its weights are fixed. This trained NN model will be used in the following subsections. The trained NN models will be evaluated only by means of the statistical indicator ARV (see Nijkamp et *al.,* 1996).

5.4 Spatial Forecasting Performance of the Neural Network Model

In this subsection, the predictive quality of the two NN models will be evaluated. The aim is to assess how well the model learned to approximate the unknown input-output function for arbitrary values of input values. The predictive quality will be evaluated - by means of the performance measure ARV - by using the test set which had been set apart and not yet used for the learning phase, as mentioned above. The result is the following (see Table 6):

	NN (A)	NN (B)
ARV	0.176	**0.299**

Table 6. The results of the ARV indicator for the two neural network models

The ARV indicates that both NN models perform well; however NN (A) offers better results than NN (B), analogously to the 'behaviour' of the **logit** model depicted in Table 4. As mentioned, a reason for this difference is likely the quality of the data used for NN (B), which is probably less than the quality of data set A.

6. Comparison of the Logit and the Neural Network Modelling Approaches

6.1 Comparing the Neural Network and the Logit Models

In this section, the two alternative modelling approaches, viz. the logit and the NN modelling approach, will be compared. In order to carry out this comparison, the test set that has been kept apart during the calibration procedure has been used. Both the logit and the NN models have been employed to estimate the freight flows for each link (ij). In the presentation of our empirical results we focussed rather randomly on export and import flows to and from all other European regions from three regions in The Netherlands (i.e. Breda, Eindhoven and Maastricht) for both product groups (food and chemicals), which is illustrated by Figures 2 – 25 (see Annex). In these figures the estimates made by both modelling approaches are presented as a percentage of the real flow. Lack of space does not permit a detailed discussion of all results, but largely self-explanatory. The general conclusion is that the estimates made by both the logit and the NN models are slightly lower than the real freight flows, while the NN model is in general more accurate than the logit model. However, in some cases the logit model made more accurate estimates than the NN model (e.g., see Figure 7 and 8), while Figures 6 and Figure 12 show that the estimates are higher than the real value.
The estimates for the chemical transport flows are less precise and smaller than the observed flows, in comparison to the estimates made for the food sector. In conclusion, the predictive performance of the NN model is in general slightly better than that of the logit model.

The ARV is a good measure for the goodness-of-fit of NN models and is a frequently used test statistic. This performance measure is calculated using the test set only (see Table 7).

	ARV	
	Logit	**NN**
Food	0.183	0.176
Chemicals	0.311	0.296

Table 7. Comparing logit and neural network models by the ARV indicator

The values of the ARV indicator demonstrate once more that the NN model for spatial flow forecasting performs overall slightly better than the logit models, Particularly, the NN model for food has the most accurate performance.

6.2 Sensitivity Analysis by Means of Policy Scenarios

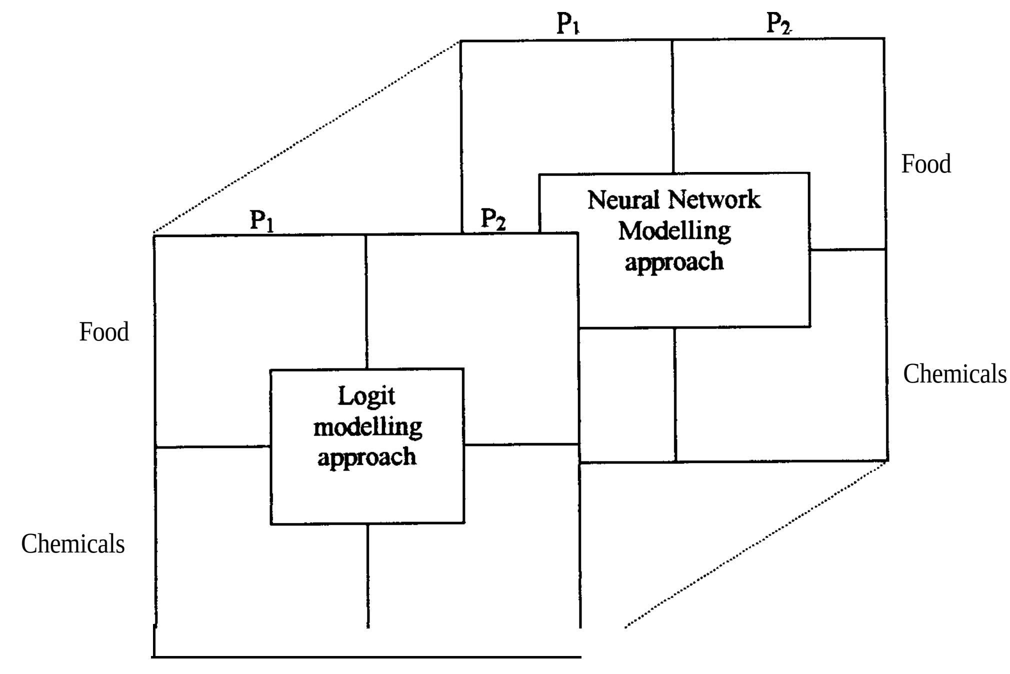
Freight transport by road causes high social costs (e.g., pollution, road maintenance), which might be charged to the transport sector. At present, because of severe problems on the road transport network (for example, congestion), governments are trying to reduce the road usage by imposing policy measures that serve to increase the cost of road usage (see Verhoef, 1996). An example of a Pigouvian policy for coping with environmental externalities is the recently increased tax on fuel in the Netherlands. In so doing, the usage of the road transport network is made less attractive than other transport networks. What are the consequences of increasing the transportation costs for freight flows using the road transport network? In this section, a sensitivity analysis of policy scenarios will be carried out by means of the two modelling approaches described above. Only the test set will be used for this analysis.
Clearly, although there is an agreement on a Common Transport Policy for the EU, the national transport policy still has significant importance in the transport network development in the EU. Because of this, two different types of policy will be considered in our sensitivity

analysis, viz. a European tax policy and a national tax policy. The first one means a cost increase for the road mode for all the transport links (ij) between the 108 European regions considered. The last one will have the same cost increase, but only for the transport links (ij) between the Dutch regions and the rest of the European regions. Since the problems on the road transport network, in particular congestion on the major freight transport routes, are believed to be increasing fast, we will vary the cost increase from 10% till 50%. The effect of a draconian measure (i.e., 50% increase in cost) can be compared against a modest policy measure. Table 8 presents the various scenarios considered in this analysis.
A national tax policy, i.e. Dutch tax policy, will be denoted as Pi and a European tax policy as P_2. The percentages of increase in the road cost, i.e. 10%, 20%, 30%, 40% and 50%, are denoted as A, B, C, D and E, respectively.

	Scenario				
	A	B	C	D	E
European tax policy	10%	**20%**	**30%**	**40%**	**50%**
National tax policy	10%	**20%**	**30%**	**40%**	**50%**

Table 8. Percentage cost increase for the road transport flows related to the scenarios

Also here both a logit and a NN model will be employed in order to predict the freight flows related to the various policy scenarios. The same selection of Dutch regions as in Subsection 7.1 will be used here in order to illustrate and compare the predictions made by the models applied. In this subsection, a comparison of the forecasting potential of the models employed for the two different scenarios (i.e., P1 and P2) and of the two commodity categories will be carried out as illustrated by Figure 1.



gure 1. Dimensions of comparison

National Dutch tax policy and European tax policy

The relative estimated chemical freight flows are presented in Figures 6, 7, 8, 9 (Breda), 14, 15, 16, 17 (Eindhoven) and 22, 23, 24 and 25 (Maastricht). These figures show that using the logit model the estimated freight flows related to P_1 are more or less identical to the freight flow related to P_2. The logit model indicates that the consequences of P1 and P_2 are largely the same. In the case of Pi, we would expected smaller freight flows, since the competitive advantage of The Netherlands, which has a lot of transit freight flows, would decrease. However the predictions using the NN model show that the estimated freight flows resulting from a European tax policy are smaller that those of a national Dutch tax policy, as we would have expected.

Food and chemical products

Comparing the estimated freight flows for both commodity, it seems that the estimates for the food flows seem to be somewhat more sensitive to changes in the 'cost' attribute than those for the chemical freight flows.

Logit models and neural network models

The NN models show that the freight flows related to a Dutch tax policy is smaller than the flows related to a European tax policy. Although the estimates of both modelling approaches are slightly sensitive to changes in the cost attributes for the road mode, the logit model appears to be slightly more sensitive than the NN model, in general.

6.3 Concluding Remarks

Our findings appear to offer a wealth of new insights. The results indicate that both modelling approaches are somewhat sensitive to changes in the cost attribute, while the logit model is slightly more sensitive overall. The NN model estimates appear to be closer to the real flows in general.

However, the above results may be considered to be rather reliable and valid, given the good performance of the calibration / test phase. Moreover, these results may offer a range of plausible values to policy actors aiming to evaluate the impact of cost changes on flows.

It is also noteworthy that on the one hand, the large amount of data at an aggregate level hampers a behavioural perspective inherent in logit models, but that on the other hand, the type of architecture adopted in NN models seems critical for the validity of the results. Consequently, the results of our model may be used as a benchmark for the results of other models.

7 Conclusions

This paper started with a concise review of European freight transport policy. Although there is a policy agreement among the members of the EU, the European Transport Policy is still not effectively and efficiently applied. National policies still have a strong influence, which results in major differences between national transport networks in Europe in both operational and organisational aspects. In order to study the complexity of such networks, a logit modelling approach is a well known and frequently applied procedure. On the other hand, the application of the NN modelling approach to transport economics is rather new and unexplored. An NN model is able to study the input-output relations when it is presented a training data set with all observed inputs and the desired output. Two different learning methods (supervised and unsupervised learning) can be used for this purpose. The cross-validation method can be used to let the NN model know when to stop the learning procedure. The advantages of applying NN models to transport economics are:

- NN models are able to map out quite complex problems due to its unique architecture;
- overcoming noise in data can be done more properly, because the NN models consist of parallel processing units and hence are better in recognising a pattern in the data set.

Some noteworthy disadvantages of NN models are:

- it is not certain that a NN model has learned correctly, since it is not known when or whether it reaches a global minimum during the training procedure;
- the knowledge, which is stored in its weights after the training is done, is not easily understood.

From the sensitivity analysis carried out here, it is clear that the NN models are able to extract more information than the conventional discrete choice models, in the case of different policy scenarios. On the other hand, the results also indicate that the logit modelling approach is slightly more sensitive to changes in the cost attribute, while the NN modelling approach appears to be fairly robust. Based on these findings, it seems likely that the NN modelling approach is more suitable for spatial forecasting of freight flows, while the logit modelling approach is more suitable for temporal forecasting. However, the predictions made by both models should be tested with more recent and accurate real space-time (pooled cross-section time-series) data to evaluate the performance more thoroughly. Clearly, to further understand the possibilities and limitations of applying NN modelling approaches to transport policy issues, more studies need to be carried out. The experiments in this paper may thus be seen as an exploratory comparison between the models investigated

Acknowledgements: The authors wish to thank Dr. Giovanni Russo (University of Utrecht) for his significant contribution.

References

Banister, D. and J. Berechman *(eds.)* (1993), *Transport in a Unified Europe: Policies and Challenges,* North-Holland Amsterdam.

Ben-Akiva, M. and S.R. Lerman (1985), *Discrete Choice Analysis Theory and Application to Travel Demand,* MIT Press, Cambridge, Mass..

COST *328* (1998), *Integrated Strategic Infrastructure Networks in Europe: Final Report of the Action,* European Communities, Brussels.

Cramer, J.S. (1991), *The LOGIT Model: an Introduction for Economists,* Routledge, Chapman and Hall Inc., New York.

Cybenko, *G.* (1988), *Continuous Valued Neural Networks with Two Hidden Layers are Sufficient*, Computer Science Dept., Tufts University.

Hebb, D.O. (1949), *The Organisution of Behaviour,* Wiley, New York N.Y..

ECMT (1995), *European Transport Trends and Infrastructural Needs,* OECD, Paris.

Fischer, M. M. and S. Gopal (1994), Artificial Neural Network: A New Approach to Modelling Interregional Telecommunication *Flows, Journal of Regional Science,* vol. 34, no. 4, pp. 503-527.

Fischer, M. M., Computational Neural Networks, in Himanen V., Nijkamp P. and A. Reggiani (eds) (1998), *Neural Networks in Transport Applications,* Ashgate, Aldershot, pp. 3-20.

Himanen, V., Nijkamp, P. and A. Reggiani (eds.) (1998), *Neural Networks in Transport Application,* Ashgate, Aldershot, UK.

Kiriazidis, T. (1994), *European Transport: Problems and Policies,* Avebury, Aldershot.

Kohonen, T. (1989), *Self-Organisation and Associative Memory,* 3rd Edition, Springer-Verlag, Berlin

Marche, R and L. Papinutti, Infrastructure Capacity and Network Access, *in* ECMT (1993), *Transport Growth* in Question, OECD, Paris.

NEA Transport Research and Training (1994), *The Design and Construction of a European Goods Flow Database,* NEA, Rijswijk.

NEA Transport Research and Training (1998), *Spatial Patterns of Transportation: Atlas of Freight Transport in Europe,* NEA, Rijswijk

McCulloch, W.S. and W. Pitts (1943), A Logical Calculus of the Ideas Immanent *in* Nervous Activity, *Bulletin of Mathematical Biophysics, 5, pp.* 115-133.

McFadden, D. (1977), Econometric Models of Probabilistic Choice, in Mansky, C.F. and D. McFadden (eds.), *Structural Analysis of Discrete Data with Econometric Application, MIT* Press, Cambridge, Mass..

Minsky, M.L. and S. Papert (1969), Perceptrons in Anderson, J. and E. Rosenfeld (eds.) (1987), *Neurocomputing,* MIT press, Cambridge, Mass., pp 16 l-170.

Nijkamp, P. and Reggiani, A (1992), *Interaction, Evolution and Chaos in Space,* Springer-Verlag Berlin.

Nijkamp, P., Reggiani, A and T. Tritapepe (1996), Modelling Inter-Urban Transport Flows in Italy: A Comparison between Neural Network Approach and Logit Analysis, *Transportation Research C*, vol 4, pp. 323-*338.*

Reggiani, A. and T. Tritapepe (1997), Neural Networks and Logit Models to Commuters' Mobility in the Metropolitan Area of Milan in Himanen, V., Nijkamp, P. and A Reggiani (eds) (1998), *Neural Networks in Transport Applications,* Ashgate, Aldershot.

Rosenblatt, F. (1962), The Perceptron: A Probabilistic model for information storage and organisation in the brain in Anderson, J. and E. Rosenfeld (eds.), *Neurocomputing,* (1988), MIT Press, Cambridge, Mass., pp 92-114

Russel, S.J. and P. Norvig (1995), *Artificial Intelligence: A Modern Approach,* Prentice Hall, Toronto.

Schintler, L. A and 0. Olurotimi (1998), Neural Networks as Adaptive Logit Models, in Himanen, V., Nijkamp, P. and A Reggiani (eds.), *Neural Networks in Transport Applications,* Ashgate, Aldershot, pp. 13 l-150.

Tavasszy, L. A (1996), *Modelling European Freight Transport Flows,* Delft University of Technology, Delft.

Turban E. (1995), *Decision Support System and Expert System,* Prentice Hall, Englewood Cliffs, New Jersey

Verhoef, E.T. (1996), *The Economics of Regulating Road Transport,* Edward Elgar, Cheltenham, UK.

De Wit, J. and H. *van* Cent (1996), *Economie en Transport,* Uitgeverij Lemma B.V., Utrecht.

Annex Statistical Indicators and Figures

The Correlation Coeffkient (R^2)
The Statistical indicator R^2 is defined as:

$$R^2 = \frac{\sum(\bar{y}-\hat{y})^2}{\sum(y-\bar{y})^2} \tag{A1}$$

where

Y = the observed probability;

$\hat{y}$ = the probability, estimated by the adopted model;

$\bar{y}$ = the average of the observed probability.

The R^2 indicator, with $0 \le R^2 \le 1$, is usually used as a performance measurement for (linear) regression models. When the R^2 indicator approaches 1, it indicates a better performance.

The Average Relative Variance (ARV)
The Statistical indicator ARV is defined as:

$$ARV = \frac{\sum(y-\hat{y})^2}{\sum(y-\bar{y})^2} \tag{A2}$$

The ARV indicator is widely used in the neural network literature (see Fischer and Gopal, 1994) in order to test the performance of the trained NN models. This formulation of ARV implies that if the estimated mean of the observed data is used to make predictions, ARV would be equal to 1. Thus the ARV should ideally approach 0.

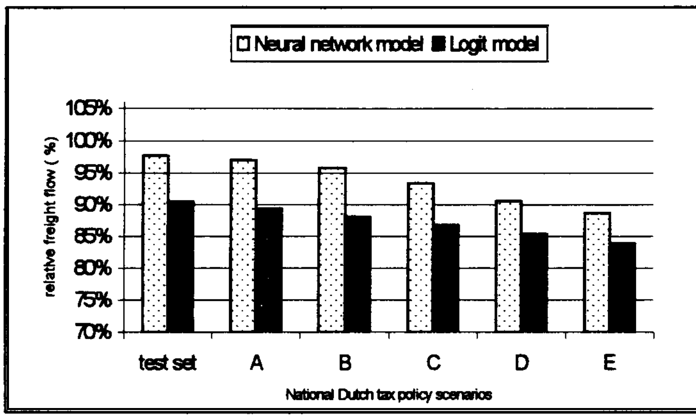


Figure 2. Estimated food freight flows from Breda to European regions

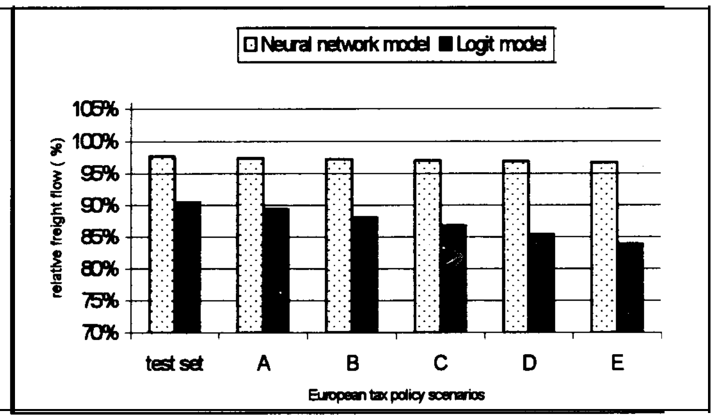


Figure 3. Estimated food freight flows from Breda to European regions

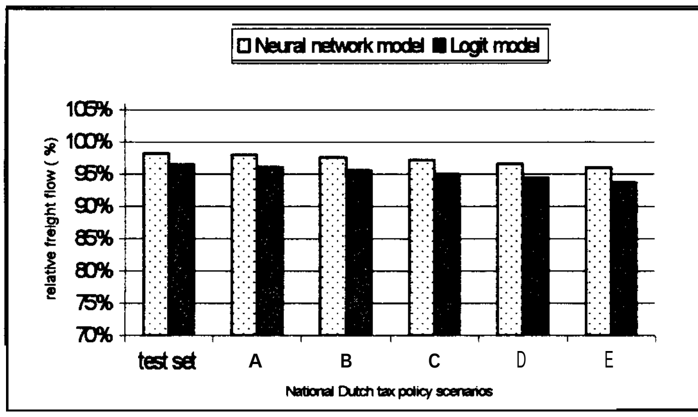


Figure 4. Estimated food freight flows from European regions to Breda

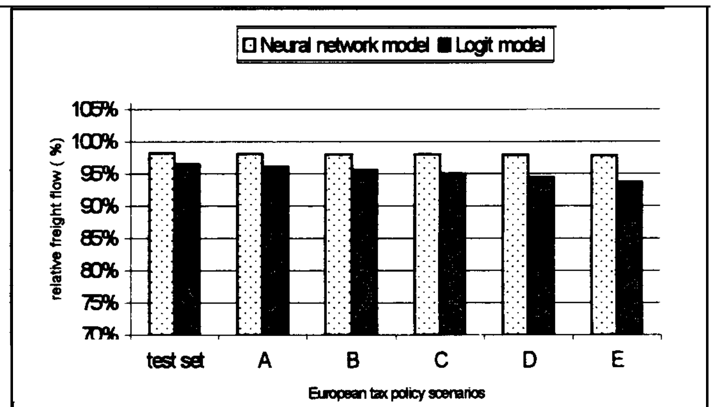


Figure 5. Estimated Rod **freight flows from European regions to Breda**

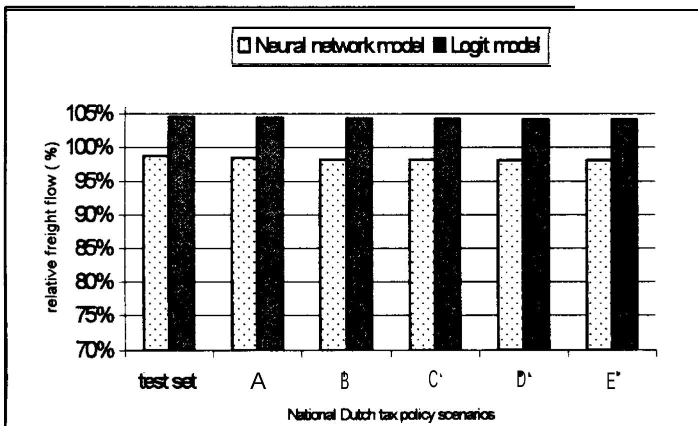


Figure 6. Estimated chemical freight flows from **Breda to European regions**

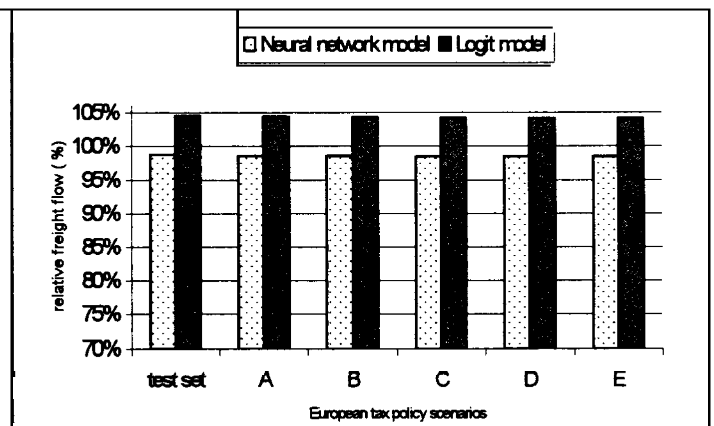


Figure 7. Estimated chemical **freight** flows from **Breda** to **European regions**

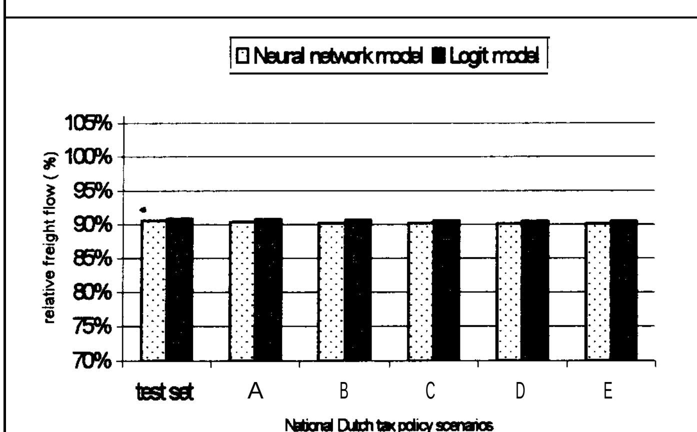


Figure 8. Estimated chemical **freight flows** from **European regions to Breda**

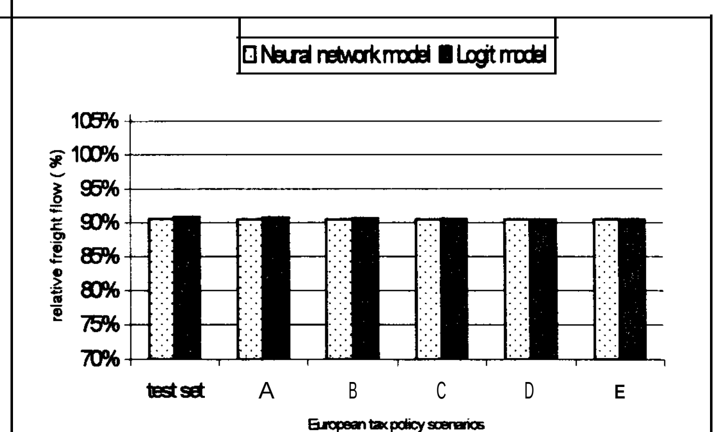


Figure 9. Estimated chemical freight flows from **European regions to Breda**

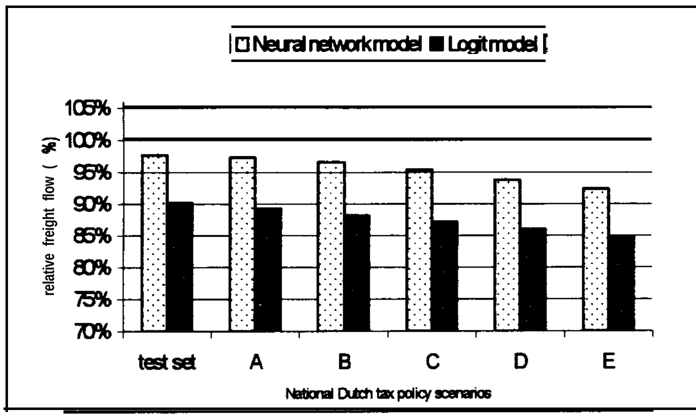


Figure 10. Estimated food freight flows from Eindhoven to European regions

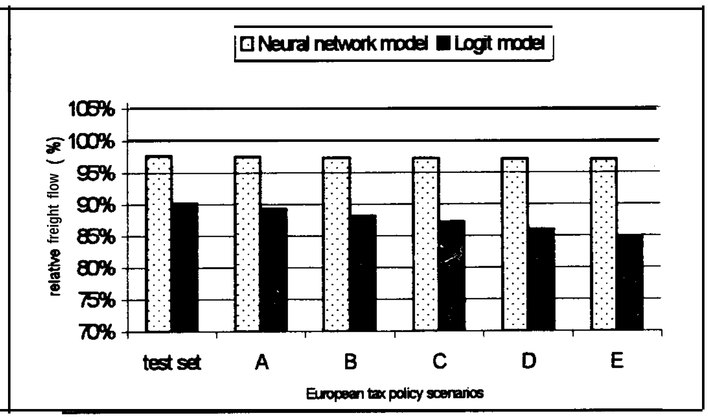


Figure 11. Estimated food freight flows from Eindhoven to European regions

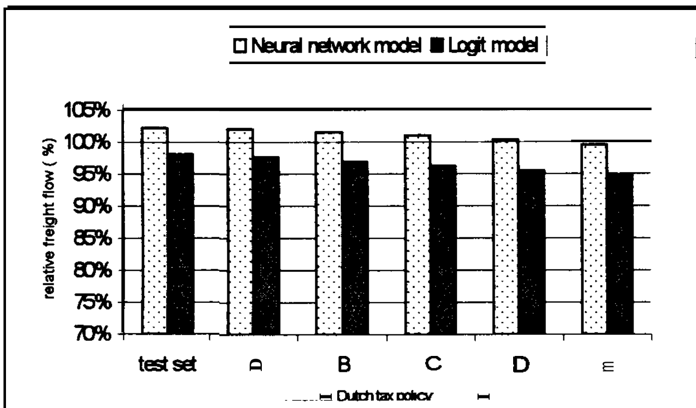


Figure 12. Estimated food freight flows from European regions to Eindhoven

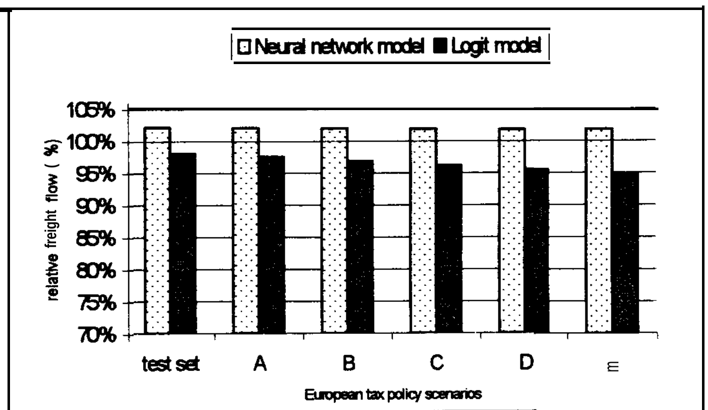


Figure 13. Estimated food freight flows from European regions to Eindhoven

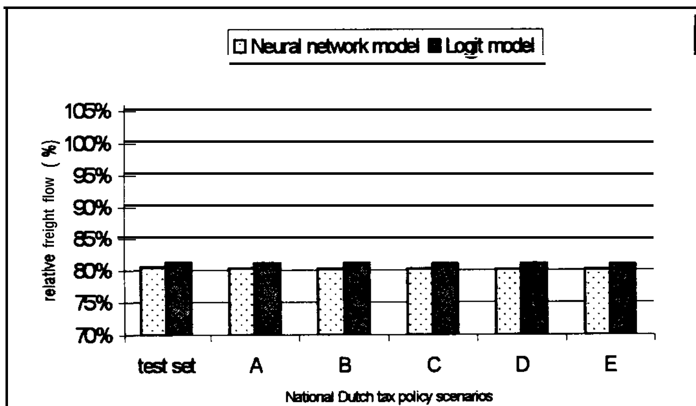


Figure 14. Estimated chemical freight flows from Eindhoven to European regions

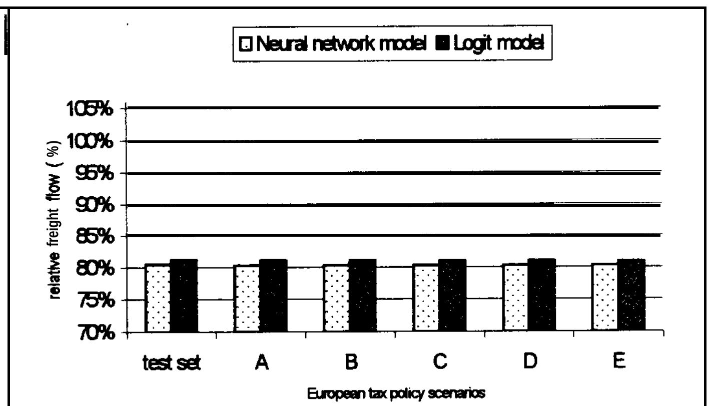


Figure 15. Estimated chemical freight flows from Eindhoven to European regions

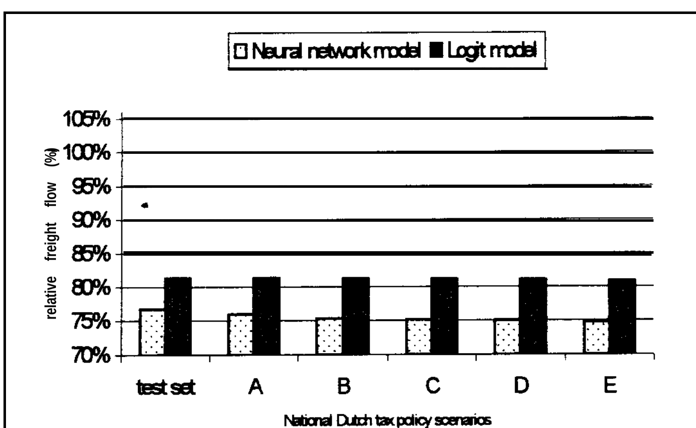


Figure 16. Estimated chemical freight flows from European regions to Eindhoven

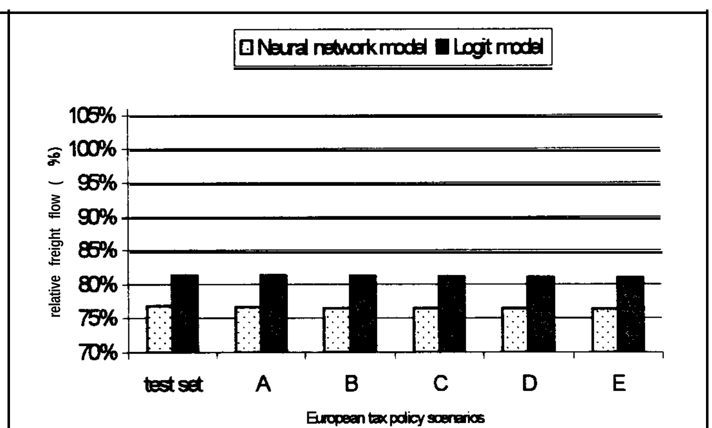


Figure 17. Estimated chemical freight flows from European regions to Eindhoven

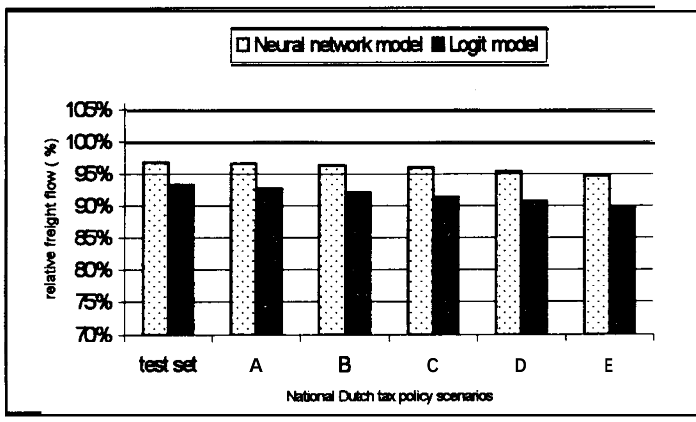


Figure 18. Estimated food freight flows from Maastricht to European regions

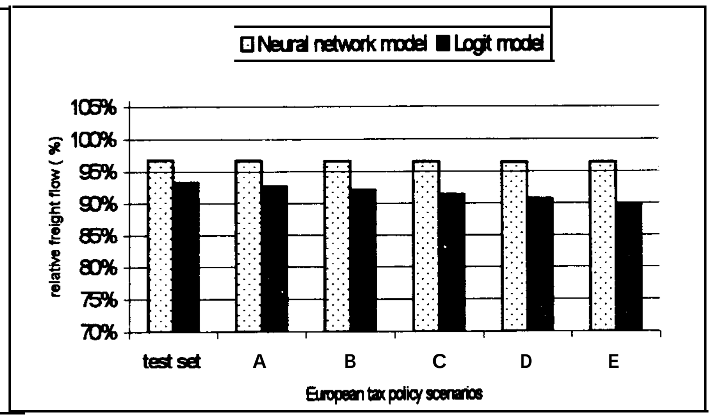


Figure 19. Estimated food freight flows from Maastricht to European regions

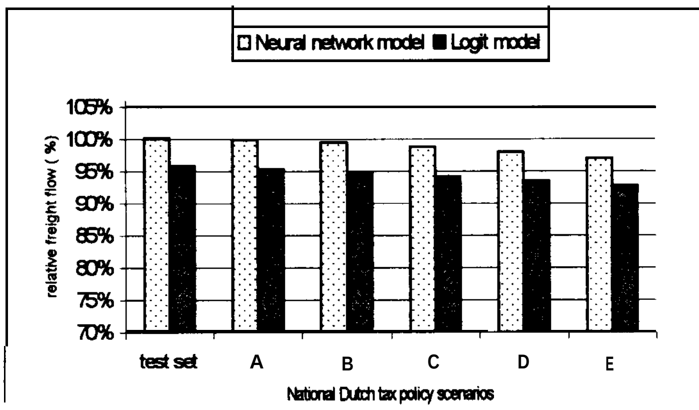


Figure 20. Estimated food freight flows from European regions to Maastricht

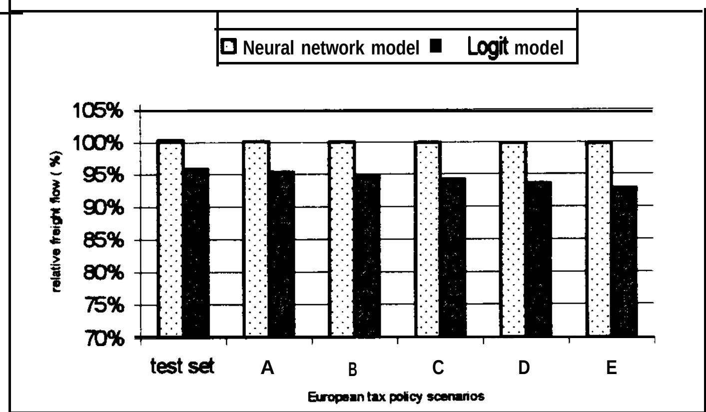


Figure 21. Estimated food freight flows from European regions to Maastricht

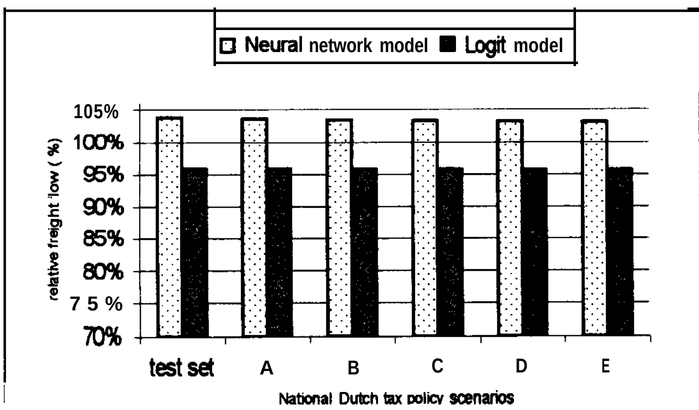


Figure 22. Estimated chemical fmiiht flows from Maastricht to European regions

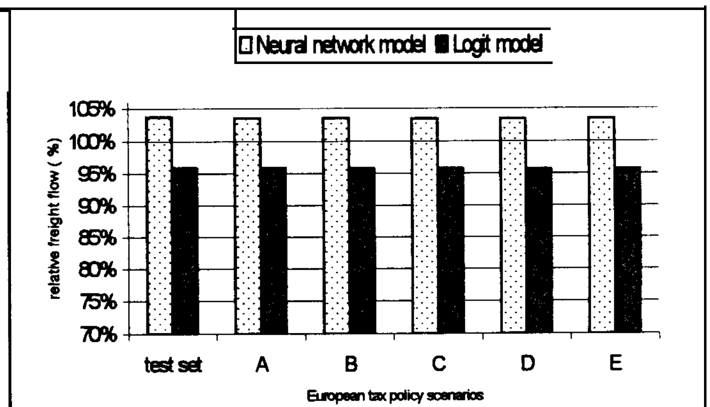


Figure 23. Estimated chemical freight flows from Maastricht to European regions

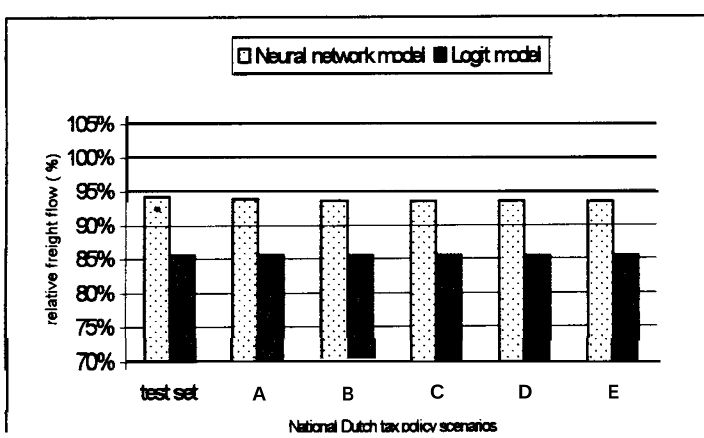


Figure 24. Estimated chemical freight flows from European regions to Maastricht

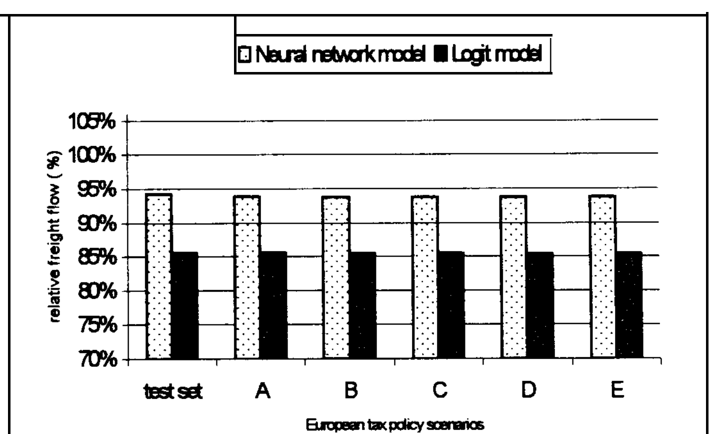


Figure 25. Estimated chemical freight flows from European regions to Maastricht